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ABSTRACT

This cluster analysis was undertaken to determine whether a discrete and stable grouping of law schools exists when a variety of characteristics of the schools and their students are considered simultaneously. The first step was to identify an appropriate and meaningful set of variables on which to group or cluster the schools. The next was to select an analytical tool for quantifying similarities and differences among the schools, cluster analysis technique. Sequential agglomerative hierarchical clustering methods were used to analyze data from the entire universe of U.S. law schools. Three law schools in Puerto Rico, one school largely for part-time students, and one that did not respond to the questionnaire were omitted, for a sample of 171 law schools. The seven variables were Law School Admission Test (LSAT) mean score, grade point average, tuition, total enrollment, selectivity, percent minority students, and the faculty/student ratio. The analyses support the presence of six clusters of law schools when variables describing size, cost, selectivity, and student body characteristics are used to group the schools most similar to one another. The majority of schools (105 of 171) fell into one of two clusters, both of which tended to represent average scores on most of the clustering variables. Even so, these two clusters differ significantly form each other on every clustering variable except percentage of minority students. Results of this study show that research studies that wish to generalize their findings to all of legal education enhance their ability to do so by sampling from each of the six clusters. (Contains 9 tables, 5 figures, and 32 references.) (SLD)

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Clustering U.S. Law Schools Using Variables That Describe Size, Cost, Selectivity, and Student Body Characteristics

INTRODUCTION

The law school admission process and particularly the role of the LSAT in that process have been studied widely for more than 40 years. A common practice among these many studies is to gather data from a sample of law schools and then generalize the results from the sampled schools to all of legal education. Frequently, the sample is drawn from among those schools that meet criteria for providing an amount of data sufficient for analysis (e.g., Wightman & Muller, 1990; Rock and Evans, 1982; Pitcher, 1977; Powers, 1977). Implicit in these studies is the assumption that law schools are sufficiently similar so that legitimate generalizations can be made about the topic of study for all of legal education based on data from the schools included in the sample. Despite the fact that the 176 American Bar Association (ABA) accredited U.S. law schools have a large number of characteristics in common, not the least of which is a virtually identical first year curriculum, there are no data to support complete fungibility among the 176 schools. A number of current and anticipated research efforts supported or under consideration by the Law School Admission Council (LSAC) require greater attention to the legitimacy of generalizing from the sample to the total population of law schools.

This cluster analysis study was undertaken to determine whether a discrete and stable grouping of law schools exists when a variety of characteristics of the schools and their students are considered simultaneously. The first step was to identify an appropriate and meaningful set of variables on which to group or cluster the schools. The next was to select an analytical tool for quantifying similarities and differences among the schools. Because the focus of this investigation is evaluating the similarities across the population of schools, cluster analysis techniques as defined by Johnson (1967) were explored as a means of partitioning the schools into optimally homogeneous groups on the basis of the selected empirical measures of similarity among each school. Cluster analysis is an empirical classification methodology. The entire universe of U.S. ABA accredited law schools potentially was available for analysis, and cluster analysis proved to be an appropriate methodology. More specifically, sequential agglomerative hierarchical clustering methods were used to analyze the law school data.

METHOD

Selecting Variables that Describe Similarities Among Law Schools

Research designed specifically to describe or evaluate systematic variation among ABA accredited law schools does not seem to be available, but data about law schools provided by the ABA and by the LSAC suggest a series of variables on which law schools may differ in ways that are important to the outcomes of many research studies about legal education. Work done in other areas of higher education was reviewed for guidance about which of the available data might be most fruitful in defining the dimensions that most differentiated participating law schools. A search of the literature revealed some research that focuses on undergraduate education (Anderson, 1982 provides a review of these studies) for the purpose of defining educational climates that can be used as treatments in a variety of educational effect studies. These studies provided some guidance as to which variables might be most useful in grouping together law schools with similar educational climates. Additionally, a recent study by Shavelson et al. (1988) identified a set of variables that resulted in meaningful clustering of graduate schools of business and management.

The review of the literature combined with discussions with individuals knowledgeable about legal educations were used to define relevant dimensions of variability for the law schools included in this study. The individuals consulted were members of the LSAC Test Development and Research Committee, members of the LSAC Minority Affairs Committee, and selected other faculty, deans, or admission professionals. The initial work suggested that the dimensions that would define the most important similarities and differences among law schools are those summarized in Table 1.

Table 1

Selected Variables Used to Describe Law School Characteristics

Variable	Description
Size	
ENR90_FA	Full time fall '90 enrollment.
RATIOFS	Faculty student ratio. {SUM(ENR90_FA,ENR90PA*2/3)/FAC_FT90}
Diversity	
MF1PCT90	Percent first-year full-time minority students (YR1_FM90/YR1_FT90)
FF1PCT90	Percent first-year full-time female students (YR1_FF90/YR1_FT90)
Admissions	
ACCPCT90	Percent accepted (Naccepted/Napplicants)*100
LSAT_Md90	Median LSAT score for full time students, fall 1990 entering class
MEDFLGPA	Median UGPA for full time students, fall 1990 entering class.
Cost	
TUI_R_90	FT annual tuition and fees (residents) (1990)
PUBPRV	Status of law school (Public/Private)

Data Source

For each of the U.S. law schools included in this study, quantifiable data related to admission criteria, size, student body diversity, and cost of attending were obtained from the Official Guide to U.S. Law Schools (1990-91) (Law School Admission Council/Law School Admission Services, 1990) and from data gathered through the American Bar Association 1990 law school survey.

Selecting Law Schools

All U.S. ABA accredited law schools were considered for inclusion in this study, but a few schools ultimately were excluded. Among the schools that were not included are the three law schools located in Puerto Rico. A majority of law school classes at these schools are conducted in Spanish, and Spanish is the native language of attending students. Because of the language differences, these schools were not included in the cluster analysis. In addition, one law school that enrolls part-time students almost exclusively and one school that failed to provide data about the entering credentials of its students in response to the 1990 ABA survey were excluded. All cluster analysis procedures were carried out using data from the remaining 171 law schools.

Selecting Variables

From the initial variable list shown in Table 1, two of the variables were eliminated from the final analyses. Based on preliminary analyses, the percentage of first-year female students and status of law school (public vs private) were determined to be unusable. There was negligible between-school variance for percentage of female students, indicating that the variable would not add any information to the clustering. Status of law school (either public or private) was correlated very highly with tuition and fees so that status was a redundant variable and would not add any information to the clustering, but it would serve to weight the cost factor if this variable were retained in the analysis. The remaining seven variables were used in all subsequent analyses. The means and standard deviations across the 171 law schools included in this study on each of the seven clustering variables are presented in Table 2.

Table 2

Means and Standard Deviations for Seven Variables Used to Cluster 171 U.S. ABA Accredited Law Schools

Variable	Mean	STD
LSAT	36.6082	3.9755
GPA	3.2036	0.2264
TUITION	8179.1579	4808.0857
TOTAL ENROLLMENT	748.3860	375.6588
SELECTIVITY	0.3176	0.1104
PCT MINORITY	0.1606	0.1235
F/S RATIO	23.0291	4.3375

As is apparent from the data presented in Table 2, the variables considered in this study are reported on a variety of scales. Most importantly, Table 2 shows sizeable differences among the means and standard deviations of these variables. Because variables with large variances tend to have more effect on the resulting clusters than variables with small variances, the variables were standardized prior to the application of any of the cluster analyses. The z-score standardization procedure, setting the mean to zero and the standard deviation to one, was used to transform all the clustering variable values prior to applying any of the clustering algorithms. Standardized variable scores are reported for the between cluster comparisons as an aid to interpreting the distinguishing characteristics among clusters.

Clustering Procedures

The term *cluster analysis* is used to describe a variety of statistical methods designed to create empirical groupings of objects. The theoretical properties of the variety of algorithms that fall under this generic term are considered in detail in the broad literature on cluster analysis (Anderberg, 1973; Cormack, 1971; Everitt, 1980; Lorr, 1983). This study initially considered several of the sequential agglomerative hierarchical cluster analysis methods for analysis of the law school data. Hierarchical techniques are most appropriate when the primary goal of the study is to discover a taxonomic structure in the set of data, but may be less appropriate when used alone if the goal it to form clusters that are highly homogeneous.

Each of the hierarchical methods begins by considering each school as a separate cluster. Each level of clustering joins two clusters by selecting from among the clusters those two that are most similar. The clustering procedure continues until either a stopping rule is encountered or all of the schools have been combined into a single cluster. Some unique properties of the hierarchical clustering procedures of particular interest are (1) the clusters are always nonoverlapping, (2) once two schools become members of the same cluster, they are never again separated, and (3) with the addition of each new school to the cluster, the centroid of the cluster is recalculated. An unfortunate consequence of this latter property is that schools already in the cluster could become more distant from the centroid of the parent cluster than from the centroid of some other clusters. Thus the subsequent clusters could become increasingly heterogeneous. One remedy for this situation (Feild and Schoenfeldt, 1975) is to use a nonhierarchical clustering algorithm as a relocation procedure by which a school is reassigned to another cluster if the distance to the centroid of that cluster is less than the distance to the centroid of the parent cluster.

A review of the literature was used to select from among the many alternatives the most appropriate cluster analysis method for partitioning the data set of law schools. Ward's method followed by a nonhierarchical *k*-means procedure was identified as the method of preference, partly on theoretical grounds and partly as a consequence of a review of empirical and Monte Carlo studies evaluating the available clustering methods. Both the Ward method and the *k*-means method merge clusters in a way that will minimize the increase in the total within group sum of squares. Thus, they are both biased toward forming spheroidal clusters, the consequence of which is that the resulting clusters tend to be homogeneous.

The literature consistently supports the use of Ward's method among the many available hierarchical clustering methods. In an extensive review of clustering methods, Milligan and Cooper (1987) noted that among the hierarchical clustering procedures, single linkage, average linkage, complete linkage, and Ward's methods are the most commonly tested algorithms. They concluded that Ward's method tended to perform well in all the cases where it was tested for its ability to capture existing clusters in data. The performances of the average linkage and complete linkage methods were more erratic, while the single linkage method was repeatedly shown to provide poor cluster recovery and to be negatively affected by small amounts of error in the data. The most definitive study still is Blashfield's (1976) Monte Carlo comparison of four hierarchical clustering techniques--single linkage, average linkage, complete linkage, and Ward's methods. In that study, Ward's (1963) method was found to yield the highest accuracy. Prior to Blashfield's study, several empirical studies found some support for the relative superiority of the average linkage cluster analysis method (Cunningham & Ogilive, 1972; Rohlf, 1970; Sneath, 1966; Sokal & Rohlf, 1962).

In order to address the problem of possible heterogeneity within law school clusters generated by Ward's method, a nonhierarchical clustering algorithm similar to MacQueen's (1967) *k*-means methods was used to relocate any schools that were closer to the centroid of a different cluster than to the parent cluster to which the hierarchical method had assigned them. As noted previously, the *k*-means procedures is like the Ward procedure in that it seeks to optimize the error sum of squares and is biased toward producing spheroidal clusters. Forming spheroidal clusters of law schools using a relocation algorithm would ensure a greater degree of homogeneity among the schools in the cluster—a most desirable outcome if we want to sample from the cluster and then generate the findings to schools not selected for the sample.

Validating Cluster Results

The final step in any cluster analysis study is to validate the results. In Monte Carlo studies, the adequacy of the clustering process can be evaluated in terms of the degree to which the method(s) are able to recapture the natural structure built into the simulated data. When empirical data are used, as is the case in this study, there is no prior knowledge of the natural structure in the data, if indeed a natural structure exists at all. That is, all of the hierarchical clustering algorithms give solution partitions regardless of whether there is any true structure in the data. One way to test or validate the clustering results when empirical data have been used in the clustering process is to replicate the clustering process using a variety of clustering algorithms. Different clustering methods can, and usually do, produce different results. If the cluster structure remains fairly consistent across different clustering methods, it would support the conclusion that the clustering identified a real structure within the data, and not simply an artifact of the particular clustering method selected. To test the validity of any cluster structure suggested by the Ward method followed by a k-means relocation adjustment, the similarity of the results from each of the average linkage, complete linkage, and single linkage methods were compared with Ward's. These methods differ from one another in terms of the criterion used to determine which two clusters to merge at each level. After the 171 law schools were partitioned into clusters using each of the clustering methods, the results from the different methods were compared to determine whether the analyses had revealed real structure to the data. Two methods for relocating schools following the cluster assignments from each of the hierarchical clustering algorithms were used. First, the hierarchical method was used to assign schools to the optimal number of clusters. Using the centroids of those clusters as seeds, schools were then relocated to the nearest seed using SAS's FASTCLUS procedure. The relocation step was repeated until the change in the cluster seeds became zero. In the second method, the hierarchical clustering was stopped short of the optimal number of clusters and the centroids of the clusters formed at that point were used as starting seeds for the FASTCLUS procedure. The FASTCLUS procedure was then used to further reduce the data to the optimal number of clusters and to relocate schools assigned to those clusters until the change in cluster seeds became zero. Use of this hybrid procedure is supported by Milligan and Cooper's findings (1985) that the convergent k-means method tended to give the best recovery of cluster structure.

Description of the Four Hierarchical Clustering Methods Used in this Study

Each of the four clustering methods used in this study are described separately, with the following notation common across the four descriptions. This notation is consistent with the one used by SAS (SAS/STAT

User's Guide 1990) because the SAS PROC CLUSTER procedures were used for all hierarchical cluster analyses reported in this study.

n	number of observations (in this study, n=171 law schools)
x_i	*i*th observation
C_K	Kth cluster
N_K	number of observations in cluster K (C_K)
$\bar{X}_K$	mean vector for cluster C_K
$\lVert X \rVert$	Euclidean length of the vector **x**
$d(x,y)$	any distance or dissimilarity measure between observations or vectors **x** and **y**
D_{KL}	any distance or dissimilarity measure between clusters C_K and C_L

<u>Ward's Method</u>. Ward (1963) and Ward and Hook (1963) produced a general hierarchical clustering method that most often uses the ANOVA sum of squares to determine the clusters that should be merged at each stage. The objective is to find the two clusters whose merger results in the minimum increase in the total within groups sum of squares. For example, when clusters K and L are merged to form cluster M, the increase in the total within group error sum of squares across all clusters is

$$\Delta E_{KL} = E_M - E_K - E_L$$

where E_M = the error sum of squares for new cluster M (i.e., the sum of Euclidean distances from each data point in cluster M to the mean vector of cluster M,

E_K = the error sum of squares for cluster K, and

E_L = the error sum of squares for cluster L.

The distance between two clusters is defined as

$$D_{KL} = \| \bar{X}_K - \bar{X}_L \|^2 \; / \; (1/N_K + 1/N_L)$$

It follows that in Ward's method the distance between two clusters is the ANOVA sum of squares between the two clusters summed over all the variables. The minimum increase in the error sum of squares is proportional to the squared Euclidean distance between the centroids of the merged clusters. Ward's method tends to produce clusters with approximately equal numbers of observations, and the method is very sensitive to outliers.

Average Linkage Method. In average linkage (Sneath and Sokal, 1973), each cluster is characterized by the average of all links within it. Thus, in this method, the distance between the two clusters is the average distance between pairs of observations, one in each cluster such that

$$D_{KL} = \Sigma_i \varepsilon C_K \Sigma_j \; \varepsilon C_L \; d(x_i, x_j) \; /(N_K N_L)$$

As a result, average linkage tends to join clusters with small variances, but the method frequently produces results that are little different from those obtained with the complete linkage method.

Complete Linkage Method. In the complete linkage method, each cluster is characterized by the longest link needed to connect every member of a cluster to every other member. This method is called complete linkage because all schools in the cluster are linked to each other at some maximum distance. The distance between two clusters is defined as

$$D_{KL} = \max_{i \varepsilon CK} \max_{j \varepsilon CL} d(x_i, x_j) \; .$$

where

D_{KL} is the distance between the most distant members of clusters K and L. The interpretation of the clusters formed by complete linkage is in terms of within cluster relationships. Unlike Ward's method or the Average Linkage method, the distance between clusters does not provide particularly useful information. Like Ward's method, the results from the complete linkage method can be seriously affected by outliers.

Single Linkage Method. In the single linkage method, the distance between two clusters is the minimum distance between an observation in one cluster and observation in the other cluster. That is, the distance between two clusters is defined as

$$D_{KL} = \min_{i \in CK} \min_{j \in CL} d(x_i, x_j) \quad .$$

Despite the fact that the single linkage method has been widely studied and applied, and is both intuitively appealing and theoretically attractive, Milligan and Cooper (1987) noted in their methodology review of clustering methods that the single linkage method has been shown to give poor cluster recovery and to be seriously affected by the presence of even small amounts of error in the data. Based on the research to date, this method is expected to correlate least well with the cluster assignments produced by the other three hierarchical methods.

Determining the Optimal Number of Clusters

Hierarchical agglomerative methods do not determine the number of clusters in the data set. Thus, an external stopping rule must be applied as part of the cluster analysis procedure. The three methods for suggesting the optimal number of clusters that are available in the SAS cluster analysis program were examined for the law school clustering.

Cubic Clustering Criterion. The cubic clustering criterion (CCC) (Sarle, 1983) is one of the stopping rule statistics available in the SAS package. It is described by Milligan and Cooper (1985) as an index that is the product of two terms: the natural logarithm of $(1\text{-}E(R^2)/(1\text{-}R^2)$ and $((np/2)^{.5})/((.001+E(R^2))^{1.2})$, where R^2 is the proportion of variance accounted for by the clusters and p is an estimate of the dimensionality of the between cluster variation. The expected value of R^2 is determined under the assumption that the data have been sampled from a uniform distribution based on a hyperbox. In a study that examined thirty procedures for determining the number of clusters in a data set, Milligan and Cooper found that the cubic clustering criterion is among the best of the available options. When it was in error, it was more likely to produce too many than too few options. That is, if the index makes an error, it is more likely to result in an incomplete clustering of the data. Two procedures were incorporated into this study to guard against selecting too many clusters for the law school data. First, two alternative stopping rules were applied to the same data in order to obtain confirmation of the optimal number of clusters. Additionally, several clustering procedures were compared to determine the consistency of the clustering results.

Pseudo F. The pseudo F statistic measures the separation among all the clusters at the current level.

Pseudo t^2. The pseudo t^2 statistic measures the separation between the two clusters most recently joined.

Measuring the Similarity of Obtained Clusters across Clustering Methods

The cluster assignments resulting from application of the various clustering methods typically do not agree perfectly. However, if the methods result from a stable underlying taxonomy, rather than from an artifact of the particular method selected, there should be substantial agreement among the methods. There are several alternatives for evaluating the similarity across methods (e.g., Borko et al., 1968; Green and Rao, 1969; McIntyre & Blashfield, 1980; Rand, 1971). The Borko et al. procedure uses a simple contingency table to depict the similarity of classifications between two methods. The *c* statistic focuses on the joint membership of pairs of data in the same cluster across methods. Green and Rao's method is basically equivalent to the *c* statistic. The McIntyre and Blashfield's kappa statistic requires matching each cluster in the solution to one of the population in the mixture. The matching requirement is problematic because the way in which the matching is accomplished can severely inflate or underestimate the size of kappa.

Rand's *c* statistic was used to evaluate the clustering results for the law school data. The similarity, *c*, between two clusters L and M for the same data is defined as

$$c(L,M) = (N(N-1)/2 - \{1/2[\ \Sigma_i\ (\ \Sigma_j n_{ij})^2 + \Sigma_j\ (\ \Sigma_i n_{ij})^2] - \ \Sigma_i\Sigma_j n^2_{ij}\})/[N(N-1)/2],$$

where n_{ij} is the number of schools simultaneously in the i^{th} cluster of L and the j^{th} cluster of M. The statistic *c* ranges from 0 to 1.

RESULTS

Optimal Number of Clusters

The results from the several procedures for determining the optimal number of clusters were not perfectly consistent either across criteria within clustering method nor across methods using the same criteria. Statistics for determining the optimal number of clusters resulting from applying each of the three procedures to each of the four clustering methods (Wards' method, the average linkage method, the complete linkage method, and the single linkage method) are shown in Table 3. In order to examine the presence of an effect from outliers, each of the procedures for determining the optimal number of clusters was run twice—one time with no trimming and one time with 10 percent trimming. In order to more easily identify the optimal number of clusters suggested by each procedure, the statistics presented in Table 3 are plotted against number of clusters for values of one to 20 clusters. Plots of the cubic clustering criteria by number of clusters for each of four of the clustering analyses are shown in Figures 1a through 1d. Likewise, overlaid plots of the pseudo F and pseudo t^2 statistics by number of cluster are shown in Figures 2a through 2d. Arrows on the plots point to the optimal number of clusters suggested by each analysis. Neither the CCC nor the pseudo F statistics are included for the single linkage method. Because the single linkage method tends to chop off tails of distributions, neither of those statistics are appropriate for it. The pseudo t^2 can be used by looking for large values. The optimal number of clusters is one more than the level of the large t^2 statistic.

For Ward's method with no trimming, the CCC shows no sharp peaks and the pseudo F statistic peaks at 4 and 5 clusters. The pseudo t^2 statistic plummets at 6 and falls even lower at 12 and 19 clusters. For Ward's method with 10 percent trimming, the CCC has a peak at 6 clusters and possibly another at 11.

Table 3

Statistics for Determining the Optimal Number of Clusters

	Criteria for Selecting Optimal Cluster for Selected Clustering Method											
	Ward's Minimum Variance Method: No Trimming			Ward's Minimum Variance Method: 10% Trimming			Average Linkage Method			Complete Linkage Method		
No. of Clusters	CCC	Pseudo F	Pseudo t^2	CCC	Pseudo F	Pseudo t^2	CCC	Pseudo F	Pseudo t^2	CCC	Pseudo F	Pseudo t^2
20	4.0434	29.13	7.05	-0.0904	22.75	6.21	-3.91	20.86	1.99	1.686	26.46	5.74
19	3.702	29.37	3.17	-0.3211	23.00	7.97	-3.5314	21.69	3.69	1.9546	27.35	2.79
18	3.3898	29.68	8.55	-0.5348	23.32	6.25	-3.4645	22.28	9.91	0.7567	26.65	11.73
17	3.1139	30.11	7.28	-0.6954	23.73	6.56	-6.5266	19.96	20.08	0.9563	27.57	5.17
16	2.8508	30.61	7.71	-0.9499	24.11	5.92	-5.9374	21.08	1.99	-0.9136	26.22	16.53
15	2.3767	31.22	6.85	-1.2013	24.55	5.37	-4.8318	22.36	1.56	-1.2942	26.45	7.83
14	2.1865	31.96	9.69	-1.4952	25.01	5.77	-4.9059	23.02	8.23	-2.3366	26.03	12.6
13	1.9076	32.69	7.43	-1.7352	25.63	8.93	-4.487	24.34	3.96	-2.1273	27.23	3.17
12	1.6004	33.5	3.87	-1.9177	26.42	9.44	-7.4693	21.82	24.22	-4.2819	25.56	16.93
11	0.964	33.97	12.95	-2.1265	27.07	9	-15.2079	14.73	47.62	-4.1403	26.86	8.67
10	0.0727	34.22	6.11	-2.9084	27.32	11.38	-14.7957	15.82	3.79	-5.4334	26.45	12.45
9	-0.5561	34.96	14.81	-3.5198	27.96	8.56	-12.5915	17.41	3.16	-4.8045	27.98	6.8
8	-1.3183	35.68	18.64	-4.2343	28.68	12.2	-13.4715	17.34	15.69	-5.7389	28.2	16.08
7	-1.9883	36.88	15.02	-4.8221	29.87	12.36	-12.6502	19.63	4.22	-5.1073	31.26	3.87
6	-2.7156	38.41	9.17	-4.9451	31.31	12.81	-16.5295	15.66	27.01	-4.4133	35.12	8.34
5	-3.5027	40.47	22.64	-5.7469	33.03	14.57	-18.0069	14.89	13.98	-10.1446	27.56	42.23
4	-4.7892	40.75	27.00	-5.643	35.74	14.37	-15.0276	17.61	6.38	-12.0354	23.73	29.02
3	-7.0709	35.55	44.02	-5.6956	38.64	21.81	-13.2892	16.97	16.17	-8.9237	29.68	11.75
2	-6.7194	31.37	35.23	-5.0316	36.64	34.49	-12.8515	4.22	29	-6.6385	31.76	26.27
1	0	.	31.37	0	.	36.64	0	.	4.22	0	.	31.76

Figure 1a

Ward's Method -- No Trimming
Plot of CCC by Number of Clusters

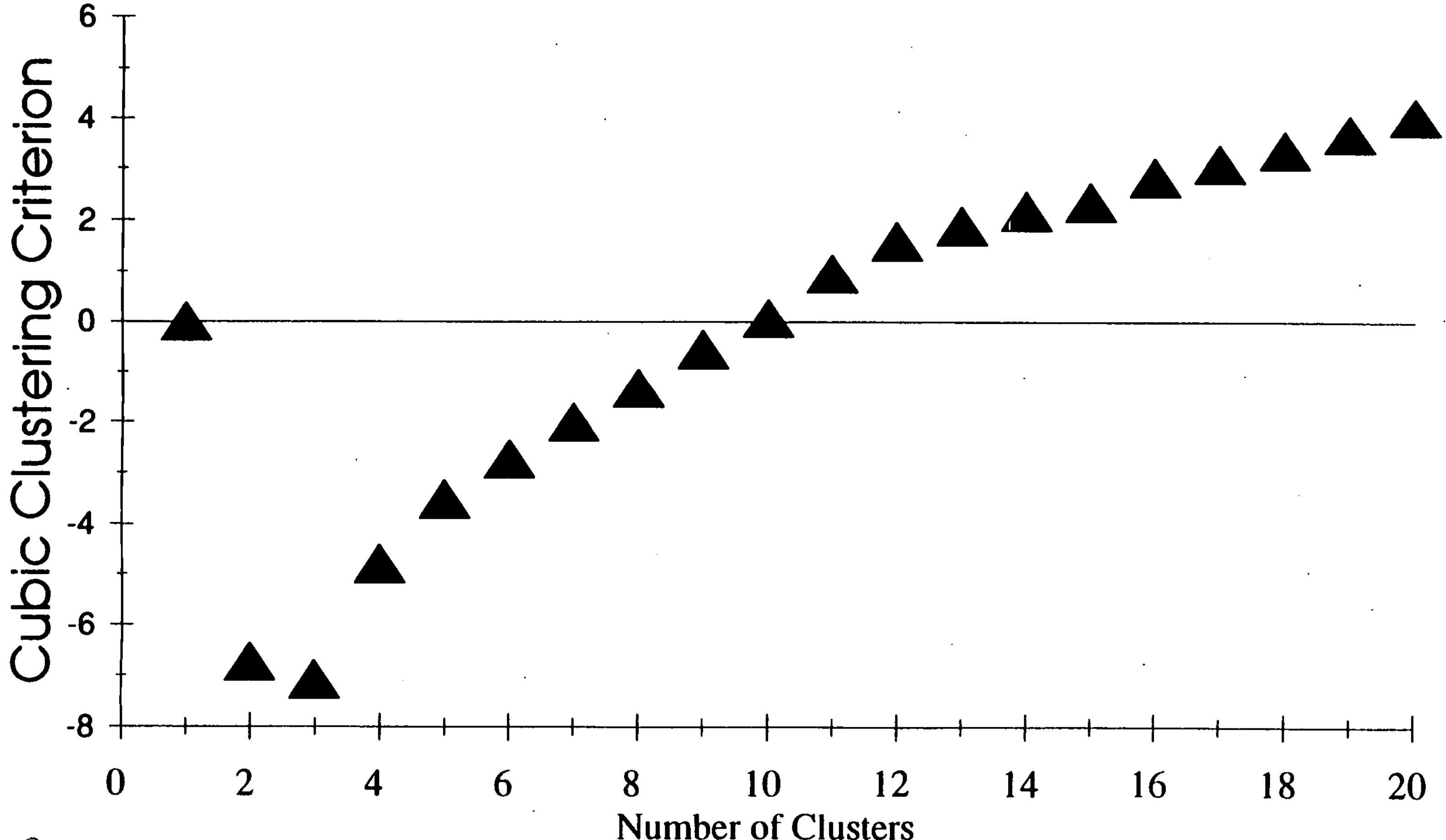

Figure 1b

Ward's Method--With Trimming
Plot of CCC by Number of Clusters

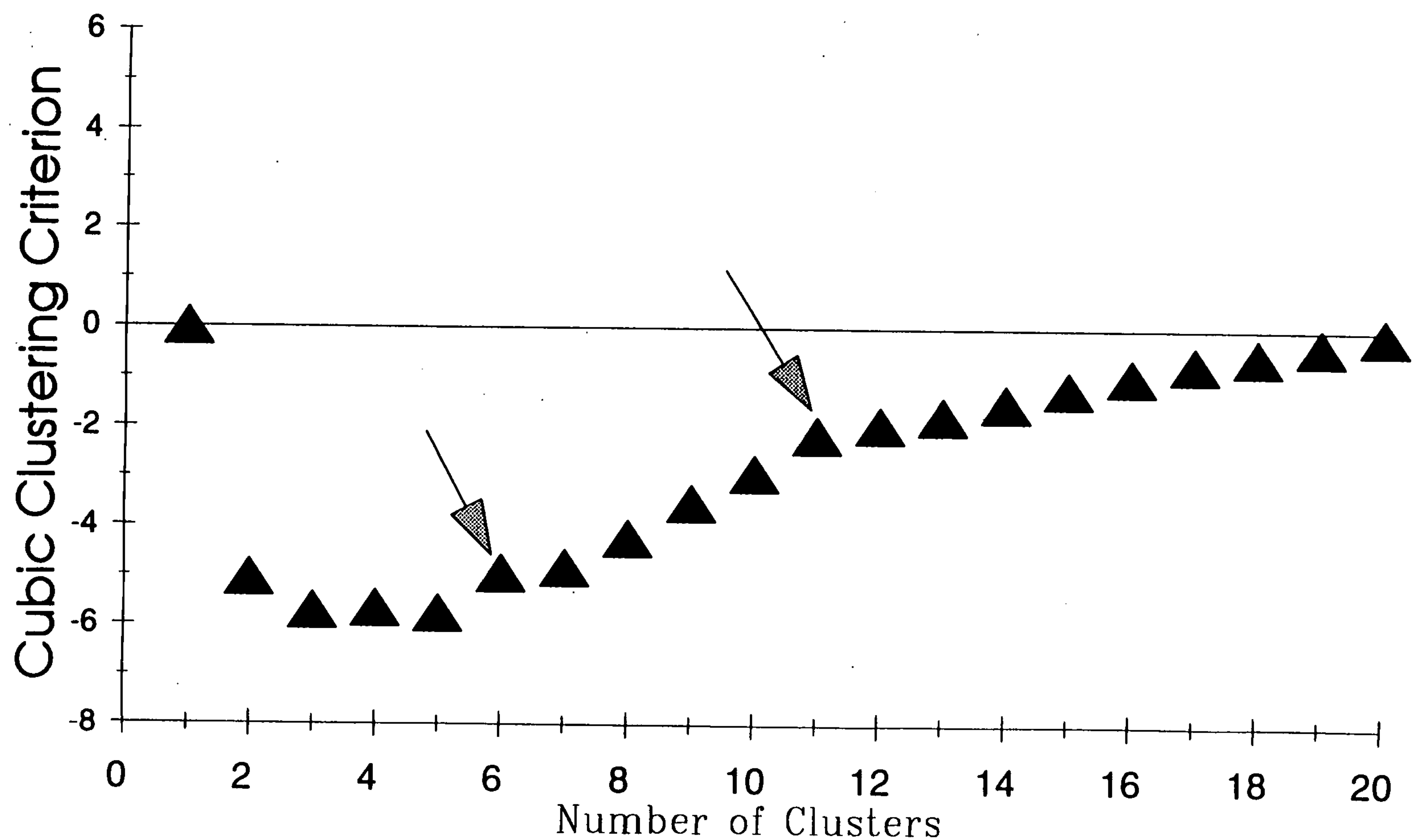

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Figure 1c

Average Linkage Method
Plot of CCC by Number of Clusters

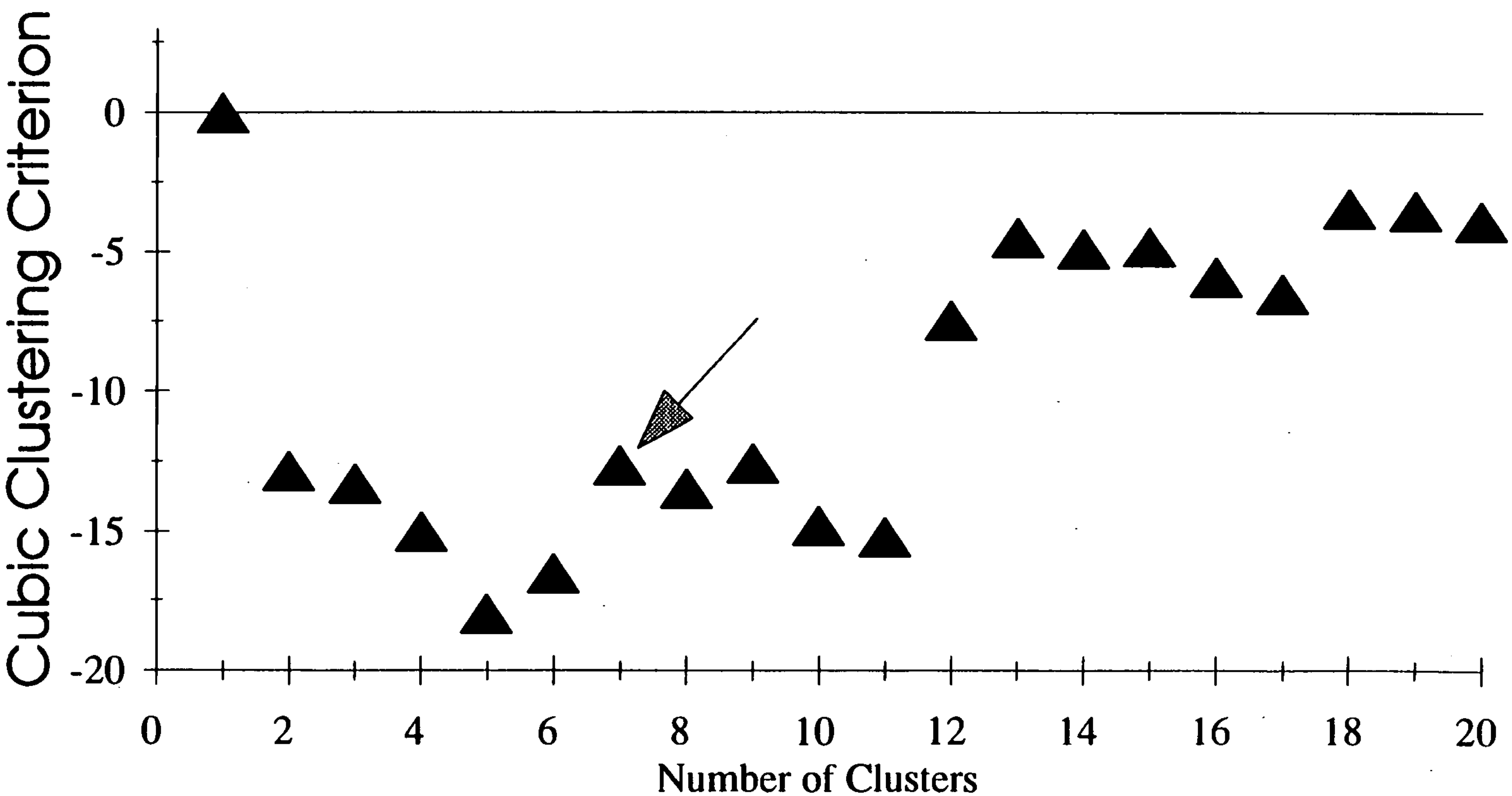

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Figure 1d

Complete Linkage Method
Plot of CCC by Number of Clusters

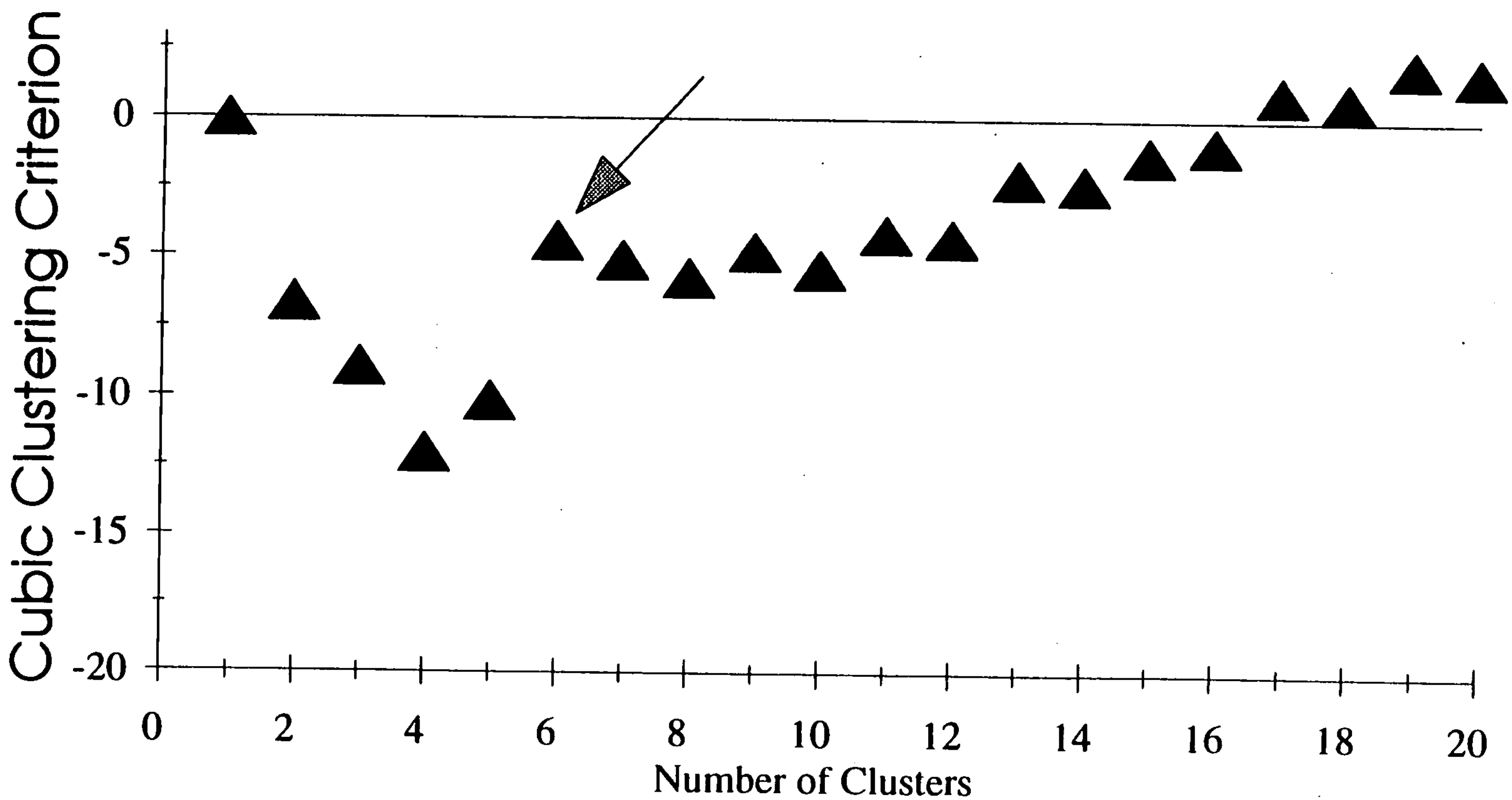

Figure 2a

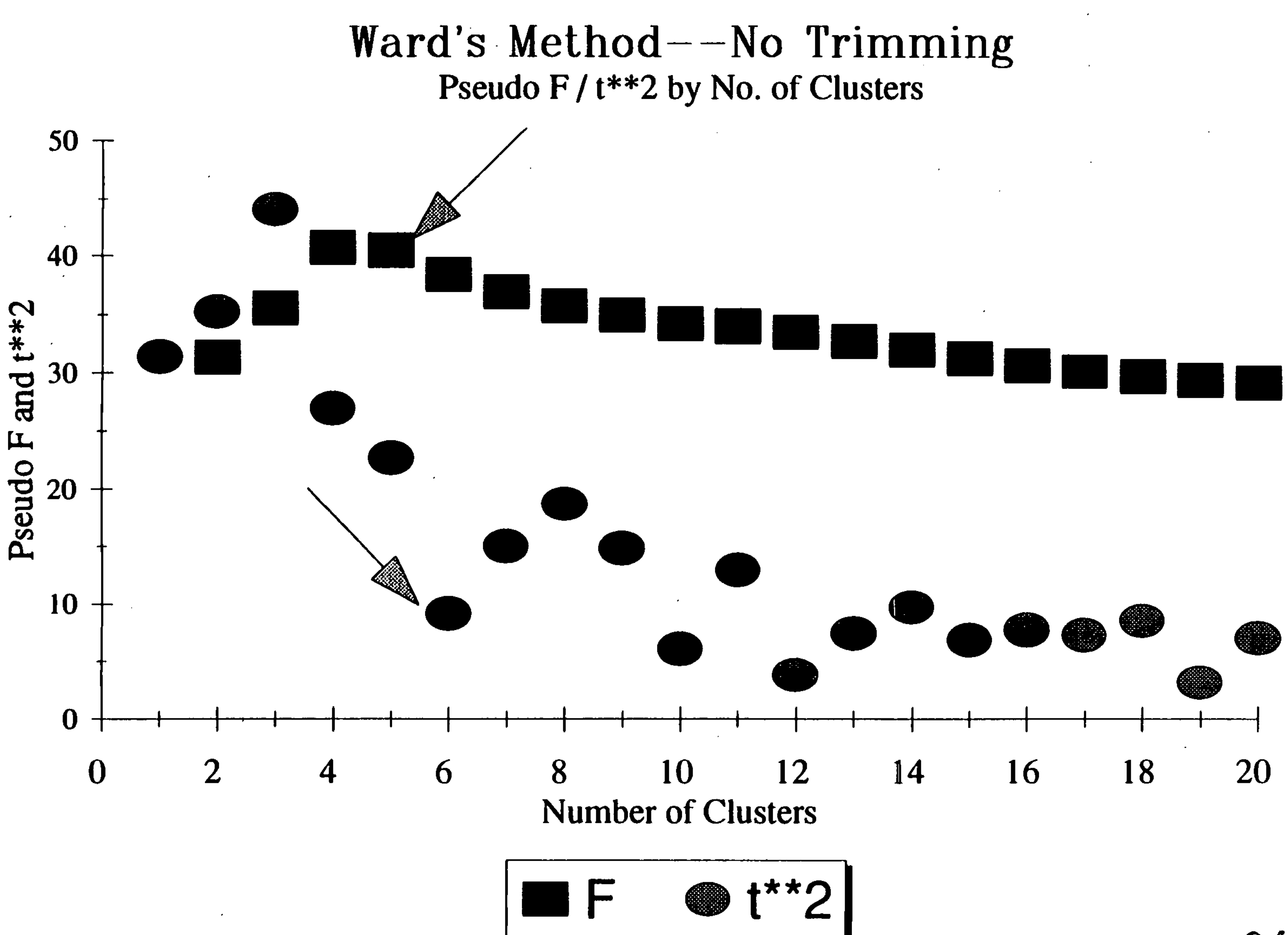

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Figure 2b

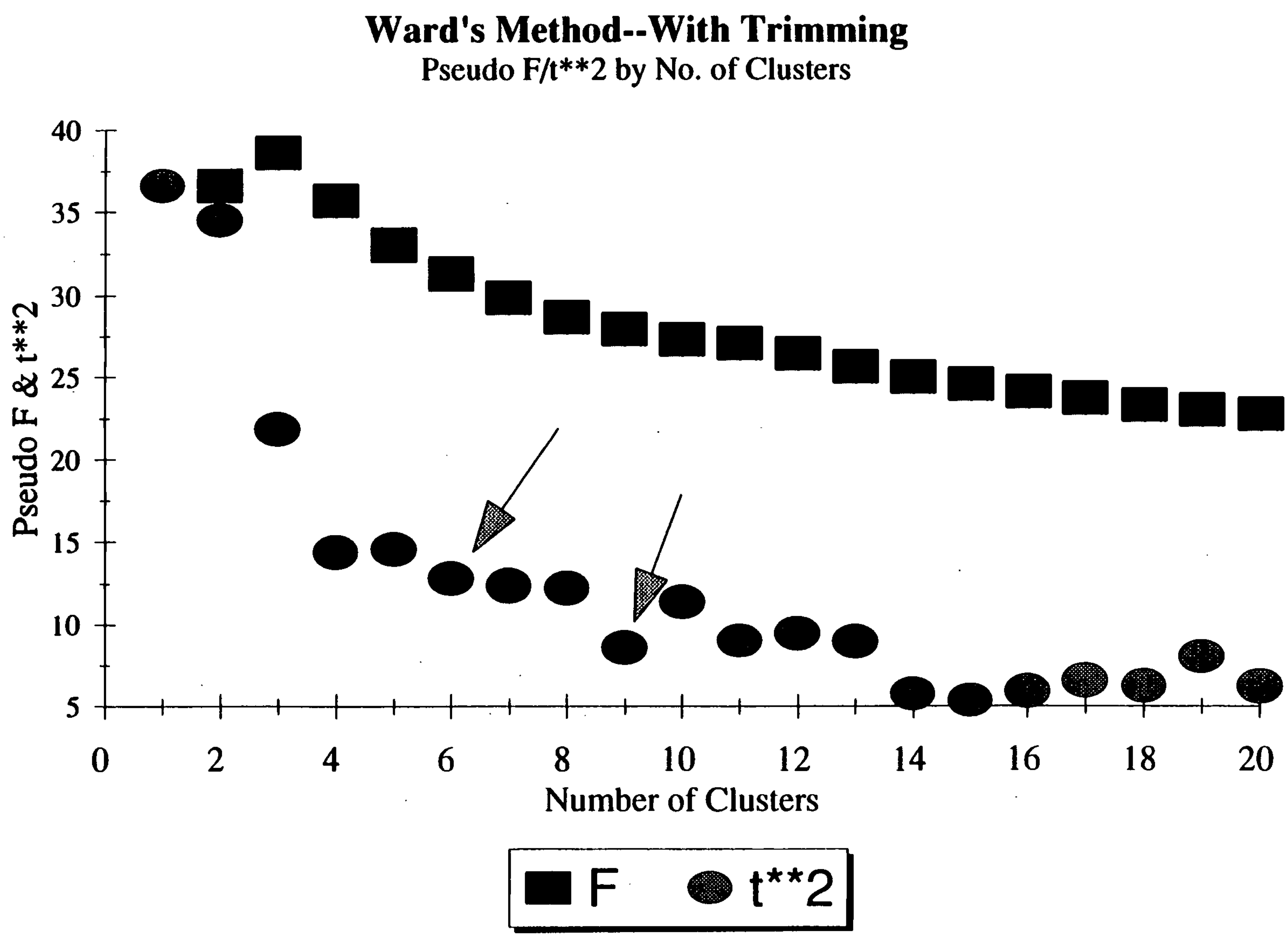

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Figure 2c

Average Linkage Method

Pseudo F/t**2 by No. of Clusters

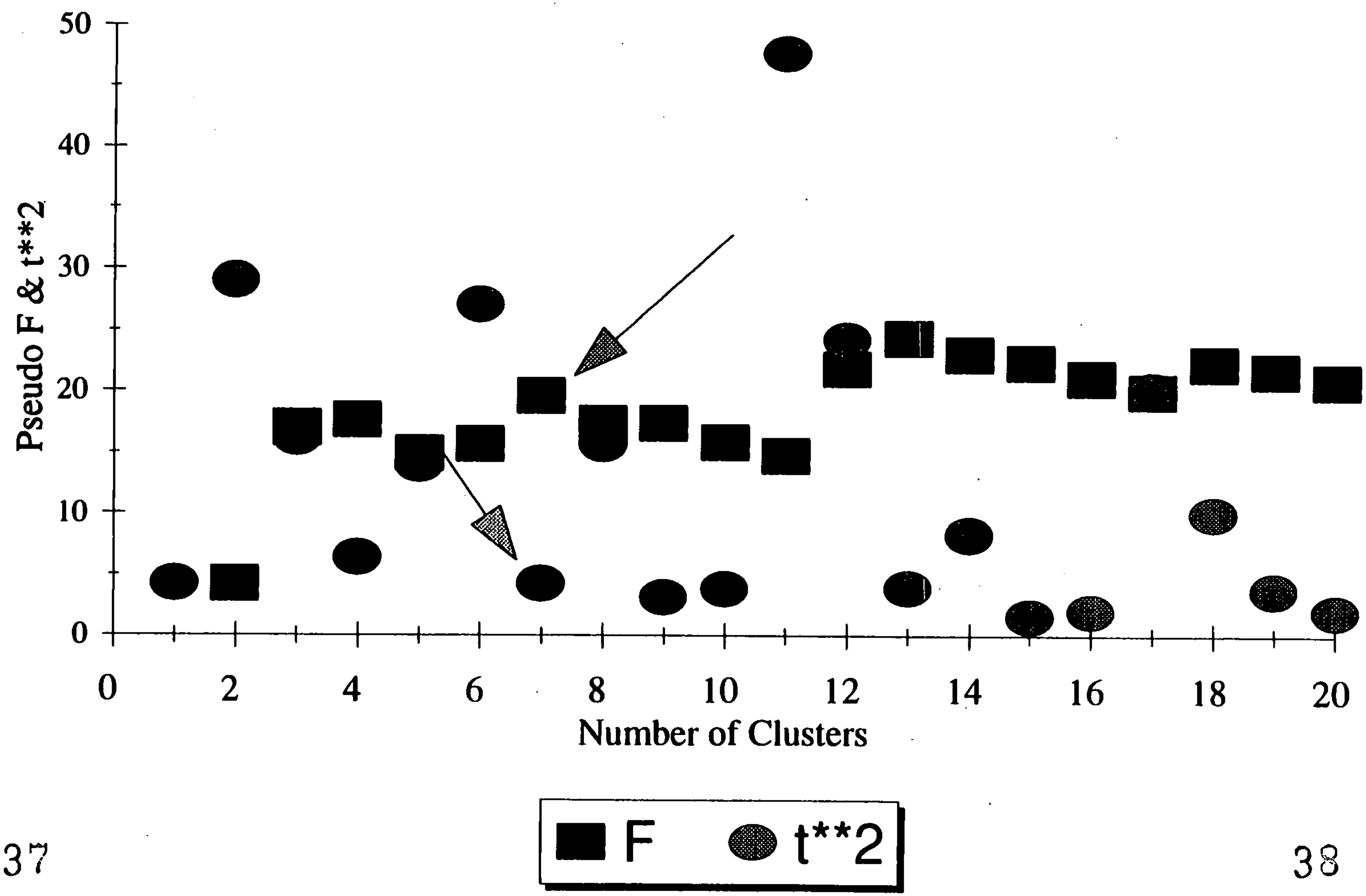
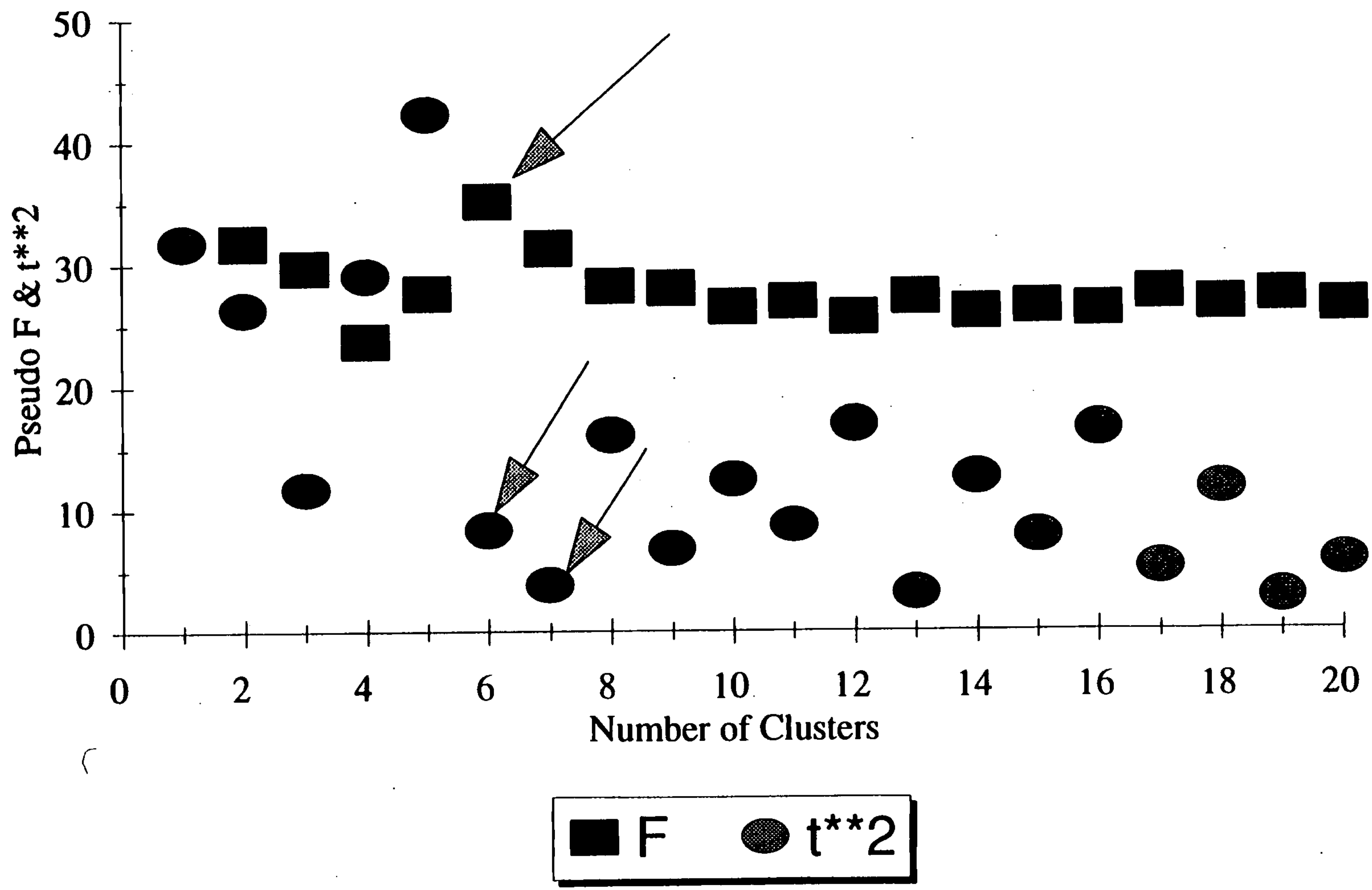


Figure 2d

Complete Linkage Method
Pseudo F/t**2 by No. of Clusters



The pseudo F statistic peaks only at 3 clusters, but the pseudo t^2 drops at both 6 and 9 clusters. The CCC has a sharp peak at 7 and 13 for the average linkage method. Consistent with the suggestion of 7 clusters by average linkage, the pseudo F for that method peaks at 7 and 13 and the pseudo t^2 statistic drops at 7 and 13. Notice that the pseudo t^2 drops to its lowest point at 15 clusters. For the complete linkage method, the CCC peaks at 6 and again at 13. The pseudo F statistic peaks only at 6, while the t^2 statistic drops sharply at 6 clusters and falls slightly lower at 7. The t^2 statistic reaches approximately the same value at 13 clusters. For the single linkage method, the largest pseudo t^2 statistic occurs at 3 and 15, suggesting 4 or 16 clusters. The number of law schools is small enough that the value of partitioning into 13 or more clusters is questionable. There is slightly more support for 6 clusters than for 7. All subsequent analyses specified a 6 cluster solution.

Final Cluster Assignments

Law schools were assigned to one of six clusters using one of the following procedures:

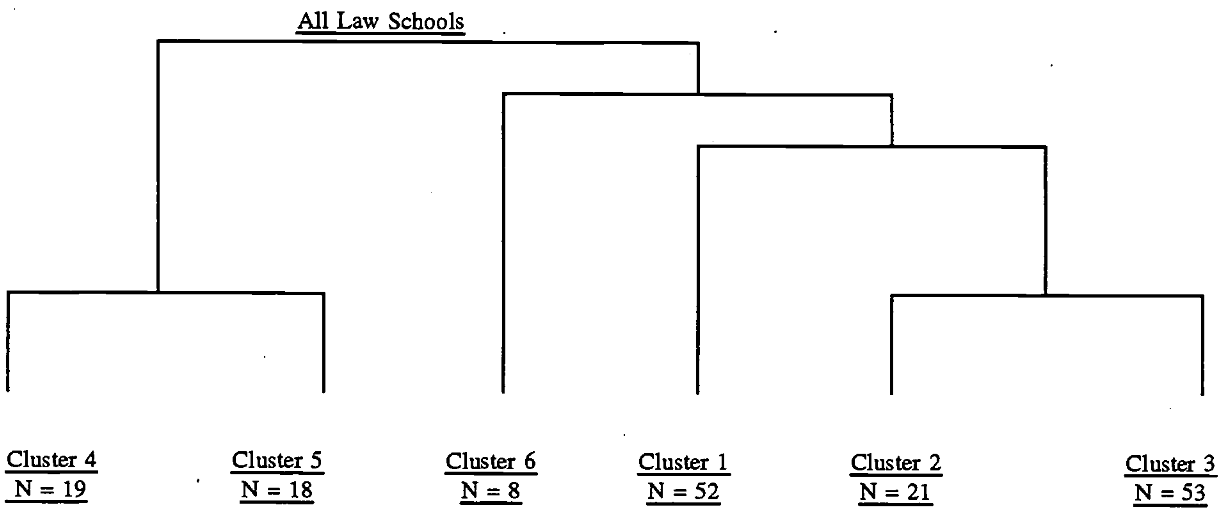
1.) Law schools were grouped into 12 clusters using each of the Ward's, average linkage, complete linkage, and single linkage methods. These twelve clusters were then relocated and fused to form six final clusters using the nonhierarchical centroid method employed by the SAS program FASTCLUS.

2.) Each of the clustering methods, Ward's, average linkage, complete linkage, and single linkage, were used to create the six clusters. The FASTCLUS procedure was then used to relocate the law schools at the same level.

The number of schools assigned to each of the six clusters that resulted from these procedures are shown in Figure 3. The dendogram shown in Figure 3 also depicts the level at which the tree structure was formed for each of the groups.

Figure 3

**Dendogram for Six Law School Clusters
Using Seven Clustering Variables**



Overlap in Clustering Methods

The Rand *c* statistic was then calculated to evaluate how well the different methods converged on a final clustering solution. The *c* statistics between each clustering method are shown in Table 4. The data suggest substantial though not perfect convergence. The clustering from Ward's 6-to-6 solution (i.e., a six cluster solution generated from the Ward's method, followed by a relocation algorithm that used the Ward six cluster solution centroids as starting seeds) correlated very highly with the results from the other solutions. As was anticipated, the single linkage method correlated the least well with the Ward 6-to-6 results. As a further check on the validity of the Ward 6-to-6 clustering results, those cluster assignments were compared with the results from the Ward's six cluster hierarchical solution with no subsequent relocation. The Rand overlap coefficient between Ward's 6 cluster solution with no further adjustments

Table 4

Rand Coefficients for Alternative Clustering Methods Each Followed by Nonhierarchical Relocation

	Ward 12	Ward 6	Ave 12	Ave 6	Compl 12	Compl 6	Sing 12	Sing 6	Centr 12	Centr 6
Ward 12		.8686	.8777	.8514	.7729	.9319	.8438	.8712	.8576	.8065
Ward 6			.9301	.9045	.8270	.8993	.7475	.7931	.8607	.8429
Ave 12				.8811	.7915	.9103	.7600	.8163	.8416	.8096
Ave 6					.8211	.9030	.7545	.8017	.8363	.8001
Compl 12						.7838	.6934	.7011	.8147	.8424
Compl 6							.8008	.8700	.8491	.7961
Singl 12								.8863	.7822	.7340
Singl 6									.7417	.8010
Centroid 12										.8954
Centroid 6										

and Ward's 6 cluster solution with relocation is .8711. The Ward's 6-to-6 solution is used for all subsequent analyses. The strong overlap between the solutions with and without relocation in addition to the strong overlap between the 12-to-6 and the 6-to-6 solutions from the other clustering procedures provide evidence that an appropriate grouping of law schools has been identified.

Canonical Discriminant Analysis of Law School Clusters

In order to obtain a graphical display of the relationships within and among the clusters, a canonical discriminant analysis of the law school clusters was conducted. That is, for the seven clustering variables and the six cluster groups, a discriminant analysis was carried out using the canonical correlation approach. The canonical correlations and the standardized canonical coefficients for the seven law school clustering variables are shown in Tables 5 and 6. The R^2 between the first canonical variable and the cluster variable

Table 5

Canonical Correlations Between the Sets of Seven Law School Clustering Variables and Six Law School Clusters

	Canonical Correlation	Adjusted Canonical Correlation	Approx Standard Error	Squared Canonical Correlation	Eigenvalue
1	0.895915	0.887359	0.015135	0.802663	4.0675
2	0.825188	0.811926	0.024471	0.680936	2.1342
3	0.778320	0.776023	0.030235	0.605782	1.5367
4	0.670198	0.670032	0.042247	0.449166	0.8154
5	0.378857	0.373286	0.065688	0.143533	0.1676

Table 6
Total-Sample Standardized Canonical Coefficients for Seven Law School Clustering Variables

	CAN1	CAN2	CAN3	CAN4	CAN5
LSAT	0.419182876	-0.214128179	-0.937669174	-0.260321032	-0.229521517
GPA	0.228077224	0.293860145	-0.048892147	-0.132765087	1.316843530
TUITION	1.080712191	0.293860145	1.169464143	-0.853444366	0.247582160
TOTENR	0.411340396	-0.082980128	0.55057676	1.346156756	0.146842638
SELECT	-0.411206166	-0.947463867	0.354536951	-0.006142111	1.057183410
PCTMIN	-0.989956539	1.226197447	0.511452388	0.112799907	0.457025577
FSRATIO	0.368843162	0.094883049	0.172380460	0.205143215	-0.257461233

is .8027, which is slightly higher than the corresponding R^2 for the second canonical variable, .6809, suggesting that the first canonical variable has slightly more discriminating power than the second. The plot of the first two canonical variables (Figure 4) shows the discriminating power for both canonical variables. The data in Figure 4 demonstrate that clusters 2 and 6 are the most widely separated by the first and second canonical variables. Cluster 6 schools have the lowest values on the first canonical function and the highest on the second. Because the R^2 for the third canonical variable is almost as large as the R^2 for the second canonical variable, the third variable was plotted against the first canonical variable and is shown in Figure 5. The standardized means on each of the clustering variables for each cluster aid in understanding the relative positions of the six clusters seen in Figure 4 and Figure 5. These means are discussed more in detail in the next section of this report.

Figure 4
Plot of Canonical Variables Identified by Cluster Analysis Using Ward's Method Followed by Relocation

Plot of CAN2*CAN1. Symbol is value of CLUSTER.

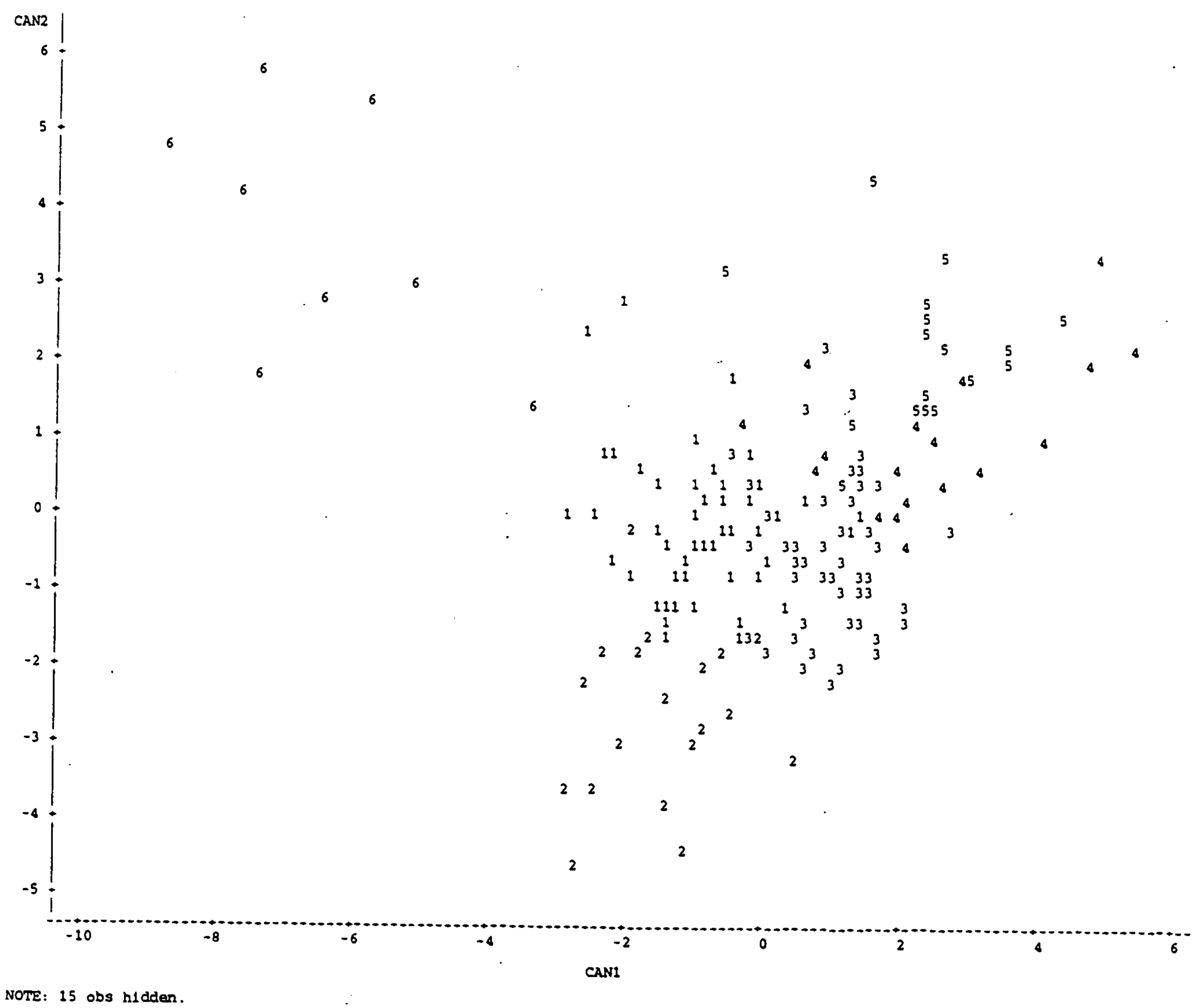


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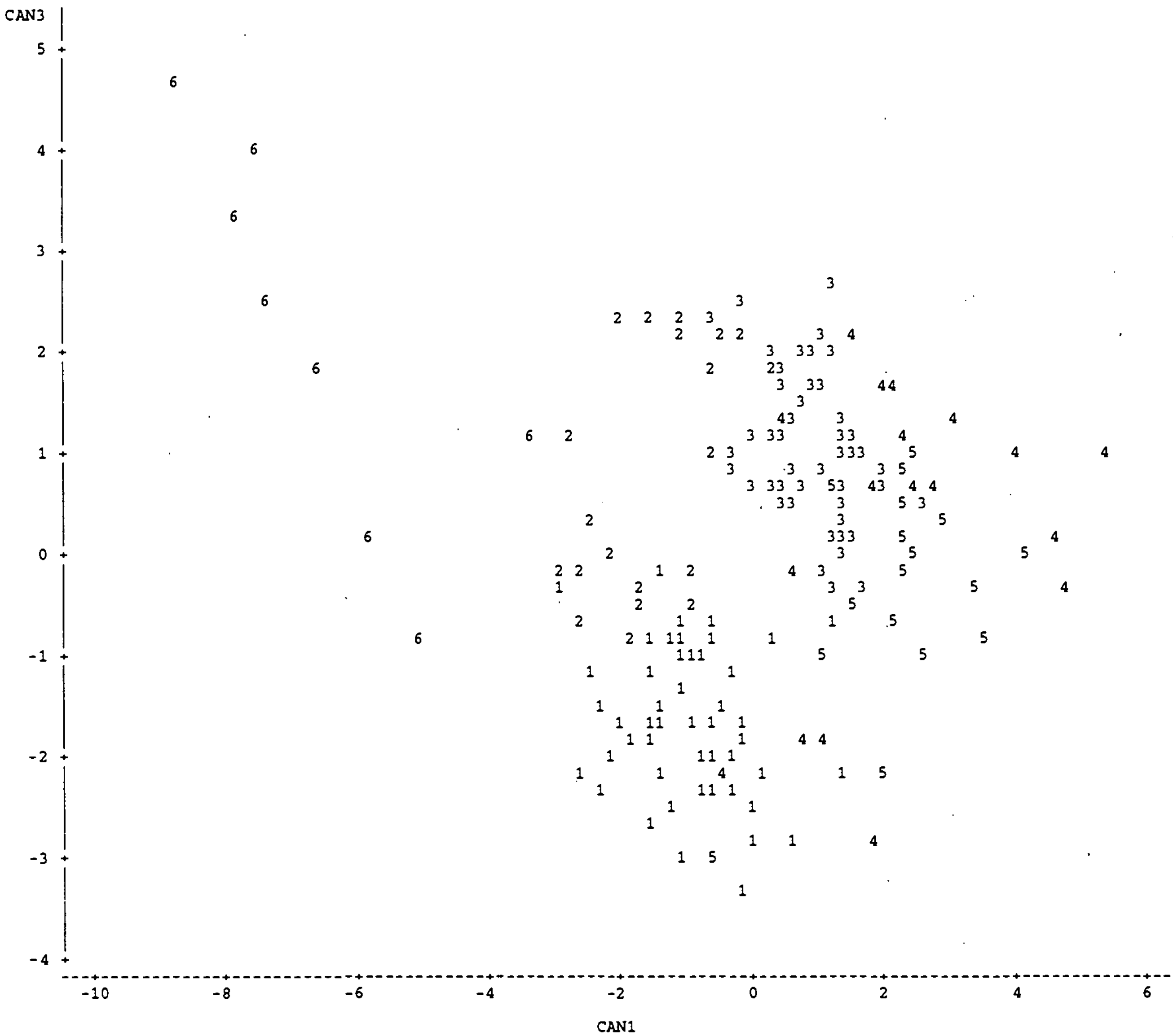
Figure 5

Plot of Canonical Variables Identified by Cluster Analysis Using Ward's Method Followed by Relocation

Plot of CAN3*CAN1. Symbol is value of CLUSTER.



NOTE: 14 obs hidden.

Comparisons Among Clusters

As an aid to describing the similarities and differences among the six clusters of law schools, a multivariate analysis of variance was carried out using the seven variables included in the vectors used to form the clusters. Not surprisingly, the differences among the clusters are highly significant. Individual ANOVA's and post hoc comparisons using the Tukey-Kramer method for unequal sample sizes (Tukey, 1953; Kramer, 1956) were used to identify differences between the clusters on specific variables.

The results from these analyses are shown in Table 7 and Table 8. The means for each of the seven variables are shown for each cluster in Table 7. Comparisons of the differences between standardized means among the clusters are shown in Table 8. All the variables are standardized to mean 0, standard deviation 1.

Table 7

Standardized Means for the Seven Clustering Variables by Cluster

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
LSAT	0.2630	-1.0873	-0.2764	0.7340	1.3702	-1.8508
GPA	0.3597	-0.6911	-0.5002	0.6091	1.2914	-1.5176
TUITION	-0.9771	-0.4237	0.6759	0.6187	1.1399	-1.0487
TOTENR	-0.3776	-0.6184	0.1312	1.9121	-0.1180	-1.0668
SELECT	-0.3215	1.6871	0.2474	-0.4885	-1.3021	0.1123
PCTMIN	-0.0997	-0.6600	-0.3591	0.2552	0.3281	3.4154
FSRATIO	-0.4346	-0.3213	0.3921	1.1782	-0.2284	-1.2133

Table 8

Comparison of Differences of Standardized Means Among Clusters

Cluster Comparison	LSAT	UGPA	TUITION	TOTENR	SELECT	PCTMIN	FSRATIO
1 - 2	1.350*	1.051*	-0.553*	0.241	-2.009*	0.560*	-0.113
1 - 3	0.539*	0.860*	-1.653*	-0.509*	-0.569*	0.259	-0.827*
1 - 4	-0.471	-0.249	-1.596*	-2.290*	0.167	-0.355	-1.613*
1 - 5	-1.107*	-0.932*	-2.117*	-0.260	0.981*	-0.428	-0.206
1 - 6	2.114*	1.877*	0.072	0.689	-0.434	-3.515*	0.779
2 - 1	-1.350*	-1.051*	0.553*	-0.241	2.009*	-0.560*	0.113
2 - 3	-0.811*	-0.191	-1.100*	-0.750*	1.440*	-0.301	-0.713*
2 - 4	-1.821*	-1.300*	-1.042*	-2.530*	2.176*	-0.915*	-1.500*
2 - 5	-2.458*	-1.983*	-1.564*	-0.500	2.989*	-0.988*	-0.093
2 - 6	0.764*	0.826	0.625	0.448	1.575*	-4.075*	0.892
3 - 1	-0.539*	-0.860*	1.653*	0.509*	0.569*	-0.259	0.827*
3 - 2	0.811*	0.191	1.100*	0.750*	-1.440*	0.301	0.713*
3 - 4	-1.010*	-1.109*	0.057	-1.781*	0.736*	-0.614*	-0.786*
3 - 5	-1.647*	-1.792*	-0.464*	0.249	1.549*	-0.687*	0.620
3 - 6	1.575*	1.017*	1.725*	1.198*	0.135	-3.774*	1.605*
4 - 1	0.471	0.249	1.596*	2.290*	-0.167	0.355	1.500*
4 - 2	1.821*	1.300*	1.042*	2.530*	-2.176*	0.915*	1.613*
4 - 3	1.010*	1.109*	-0.057	1.781*	-0.736*	0.614*	0.786*
4 - 5	-0.636*	-0.682*	-0.521	2.030*	0.814*	-0.073	1.407*
4 - 6	2.585*	2.127*	1.667*	2.979*	-0.601	-3.160*	2.392*
5 - 1	1.107*	0.932*	2.117*	0.260	-0.981*	0.428	0.206
5 - 2	2.458*	1.983*	1.564*	0.500	-2.989*	0.988*	0.093
5 - 3	1.647*	1.792*	0.464*	-0.249	-1.549*	0.687*	-0.620
5 - 4	0.636*	0.682*	0.521	-2.030*	-0.814*	0.073	-1.407*
5 - 6	3.221*	2.809*	2.189*	0.949*	-1.414*	-3.087*	0.985
6 - 1	-2.114*	-1.877*	-0.072	-0.689	0.434	3.515*	-0.779
6 - 2	-0.764*	-0.826	-0.625	-0.448	-1.575*	4.075*	-0.892
6 - 3	-1.575*	-1.017*	-1.725*	-1.198*	-0.135	3.774*	-1.605*
6 - 4	-2.585*	-2.127*	-1.667*	-2.979*	0.601	3.160*	-2.392*
6 - 5	-3.221*	-2.809*	-2.189*	-0.949*	1.414*	3.087*	-0.985

Comparisons significant at the 0.05 level are indicated by '*'.NOTE: This test controls the type I experimentwise error rate.
Alpha= 0.05 Confidence= 0.95 df= 165 MSE= 0.400533
Critical Value of Studentized Range= 4.078

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The data in Table 7 can be used to describe the similarities among the schools in each cluster. The data in Table 8 can be used to interpret the importance of the observed differences among and between clusters.

Cluster 6 includes schools with the largest proportion of minority students. The average percentage of minority students for schools in cluster 6 is significantly larger than the average percentage found among schools in any other cluster. These schools also have the lowest tuition, the smallest enrollments and the lowest faculty student ratios. Both the undergraduate grade point averages and the LSAT scores of students attending schools in cluster 6 are the lowest among any of the clusters. The comparison of differences shown in Table 7 reveal that the mean LSAT score for cluster 6 is significantly lower (alpha=.05) than the mean for each of the other clusters, while the mean UGPA is significantly lower for each cluster except cluster 2.

Cluster 4 includes the schools with the largest enrollment and the highest faculty student ratio. The means for each of these variables are significantly different from the means for each of the other clusters. The entering credentials of students attending cluster 4 schools are the second highest among the six clusters, although they are significantly lower than those of students attending cluster 5 schools and not significantly different from students attending cluster 1 schools. Cluster 4 schools are among the most highly selective, although the proportion selected is not significantly less than the proportion selected by cluster 1 and cluster 6 schools. The schools in cluster 1 have student bodies with admission credentials (i.e., LSAT scores and UGPAs) that are almost identical to cluster 4 schools. Cluster 1 and cluster 4 schools also have approximately the same percentage of accepted students. The differences between schools in cluster 1 and schools in cluster 4 primarily are size and cost, with cluster 1 schools being both significantly smaller and significantly less costly. Schools in both clusters have average, and nearly identical proportions of minority students.

Cluster 2 includes the smallest of the law schools yet the distinguishing feature of these schools is that they have the largest percentage of acceptances. That is, the proportion accepted is significantly larger than at the schools in any of the other clusters. Cluster 2 schools, which are the lowest cost schools, have students with very low entering credentials (LSAT scores and UGPAs) and they enroll the smallest proportion of minority students among all of the clusters.

The schools in cluster 5 are the most expensive. Additionally, they enroll students with LSAT scores and UGPAs that are significantly higher than those found at each of the other clusters, and accept the smallest proportion of applicants. Cluster 5 schools also enroll the second highest proportion of minority students, although the percentage is significantly less than the percentage found at cluster 6 schools.

Cluster 1 and cluster 3 include the largest number of schools—52 and 53, respectively. The schools in both clusters are about average in size, in the LSAT scores and UGPAs of their entering students, and in the percentage of students accepted. Even so, cluster 3 schools are significantly larger, significantly more expensive, and accept a significantly higher percentage of their applicants than cluster 1 schools. Cluster 1 schools are among the least expensive. Additionally, the entering credentials of students attending cluster 3 schools are significantly lower than those attending cluster 1 schools. The faculty student ratio at cluster 3 schools also is significantly higher than at schools in cluster 1. The ethnic diversity at schools in cluster 1 and cluster 3 is approximately the same, with the percentage of minority students being slightly though not significantly smaller at cluster 3 schools.

Comparisons of Nearest Centroid Law Schools

To further describe each cluster, as well as to help evaluate the homogeneity of the obtained clusters, the law school closest to the centroid of each cluster was identified. The scores on each of the seven variables for each of the nearest centroid law schools are presented in Table 9. The law school most typical of cluster 1 attracts a fairly able student body—one that presents both LSAT scores and undergraduate grade point averages more than half a standard deviation above the mean. Distinguishing characteristics of this school are its low tuition and it small faculty student ratio. Both of these factors and its relatively small size are likely related to the fact that it is among the most selective of the schools. Despite its low tuition and fees, this school has a very small percentage of minority students. In contrast to this cluster 1 school, the school most typical of cluster 4 has a student body virtually identical in terms of its entering credentials, but both size and costs that are substantially higher. Despite its increased cost, this school has far fewer faculty per student and considerably more minority students.

Table 9

Standardized Scores for Cluster Centroid Schools on Law School Variables

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
LSAT	0.6016	-1.1592	-0.4045	0.6016	1.3563	-2.1653
GPA	0.5580	-0.4577	-0.8551	0.4255	1.3087	-1.2526
TUITION	-1.0085	-0.8164	0.5243	1.0686	1.6058	-1.4892
TOTENR	-0.2672	-0.7570	-0.1687	1.5616	-0.3790	-1.1430
SELECT	-0.4313	1.3808	0.4747	-0.0689	-1.1561	0.3841
PCTMIN	-0.2476	-0.1666	-0.2476	0.4000	0.6429	2.9904
FSRATIO	-1.0765	-0.6592	0.7656	1.6118	-0.1358	-0.4909

The school at the centroid of cluster 2 is a small school with relatively low tuition and a student body with relatively low entering credentials. Its most distinguishing characteristic among the seven variables is that it is the least selective among the six centroid schools although the mean selectivity for cluster 2 confirms that this school is not the least selective among the schools that comprise that cluster. The cluster 3 centroid school also has a student body with relatively low LSAT scores and UGPAs. The cluster 3 centroid school differs from its cluster 2 counterpart in that its tuition is considerably higher, its size is smaller, and the proportion accepted is lower. The proportion of minority students is virtually identical among the cluster 1, cluster 2, and cluster 3 centroid schools.

The school nearest the centroid of cluster 4 is the largest of the nearest centroid law schools although it is not quite as large as the mean for cluster 4. Thus it is not the largest of the law schools. It is a high tuition school and it has a student body with fairly strong entering credentials. This school also has the largest faculty student ratio among the nearest centroid schools. This ratio also is nearly half a standard deviation larger than the mean for its cluster. The cluster 5 centroid school has an even more academically-able student body, as measured by LSAT score and UGPA, and it has higher tuition, but the size of this school is significantly smaller than the cluster 4 nearest centroid school. It is the most selective among the nearest centroid schools, but not the most selective school in cluster 5. This school also reports one of the largest percentages of minority students among schools not in cluster 6.

Consistent with the description of cluster 6, the school nearest the cluster 6 centroid is distinguished by the percentage of minority students it enrolls. It also is the smallest of the nearest centroid schools and has the lowest tuition. Both its size and tuition also are slightly smaller than the mean for cluster 6 schools. The mean LSAT scores and UGPAs for students at this school are the lowest among the centroid schools.

Comparison of the standardized scores on the seven clustering variables for the nearest centroid schools with the standardized means for the corresponding cluster based on all schools in the cluster confirm that the clusters are fairly homogenous and that the nearest centroid school provides a good description of the cluster. This comparison also highlights the importance of considering the statistical significance of differences as shown in Table 8 when comparing the cluster characteristics. For example, although the cluster means for LSAT scores and UGPAs are lower for cluster 1 schools than for cluster 4 schools, Table 8 suggests that these differences are not statistically significant. Table 9 shows that the LSAT scores and UGPAs for the cluster 1 and cluster 4 nearest centroid schools are virtually identical.

Summary and Conclusions

Cluster analysis methods were used to identify similarities among U.S. ABA accredited law schools. The analyses undertaken in this study strongly support the presence of six clusters of law schools when variables describing size, cost, selectivity, and student body characteristics are used to group together those schools that are the most similar to one another. The validity of the cluster assignments resulting from this study is confirmed by the strong overlap in assignments produced by each of the clustering methods.

The majority of schools (105 of 171 schools studied) fall into one of two clusters (cluster 1 or cluster 3), both of which tend to represent average scores on most of the clustering variables. Even so, the two major clusters differ significantly from each other on every clustering variable except percentage of minority students. Distinguishing characteristics for each of the other clusters are a consequence of one or more clustering variable scores that are considerably higher or lower than average law school means. For example, cluster 2 can be interpreted to represent the smallest schools with the highest proportion of accepted students, despite very low LSAT scores and UGPAs among their entering classes. Cluster 4 represents the largest of the schools. These schools are highly selective and enroll an academically able student body, although they are surpassed on both of these variable scores by cluster 5 schools. In addition to being the most selective and enrolling the most academically able student body, cluster 5 schools are the most expensive. Cluster 6 schools are distinguished by the large proportion of minority students they enroll as well as by their low cost and small size.

The results from this study confirm that law schools are not fungible in terms of several important variables that characterize their academic climates. Research studies that wish to generalize their findings to all of legal education will enhance their ability to do so by sampling from each of the six clusters. Alternatively, research studies that are designed to focus on certain characteristics of the law school environment might best be served by sampling schools from one or more clusters that best represent the characteristics of interest.

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